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A Decentralized Federated Ensemble Deep Learning Model Framework for Detection of Plant Diseases.

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Abstract
Tomato production is vital to Nigeria's agricultural economy, yet it faces severe challenges from plant diseases. This research proposes a decentralized federated ensemble deep learning model for the early detection of tomato diseases, tailored to the Nigerian farming context. Data will be sourced from local farms and public repositories, comprising tomato leaf images and crop health indicators. A deep learning architecture which combines Convolutional Neural Networks (CNN), Vision Transformers (ViT), and U-Net will be built to enhance disease detection accuracy and segmentation. To address data privacy and ownership concerns, a federated learning framework is implemented, allowing local model training without centralizing raw data. Blockchain and smart contracts will be used to ensure secure data sharing, transparent result validation, and incentivize farmer participation via a token-based reward system. Results and classification outputs will be stored using InterPlanetary File System (IPFS), providing immutable and accessible disease diagnosis. The model will be deployed on a mobile-based application which will enable real-time interaction for farmers, support informed decision-making and timely intervention. This system is expected to be a scalable, intelligent framework adaptable for broader agricultural applications that will significantly reduce yield losses, strengthen food security, and enhance economic resilience in Nigeria's tomato value chain.

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I. Introduction

The agricultural sector remains a cornerstone of global food security and economic development (Schreinemachers, *et al.,* 2018). Within this sector, tomatoes (Solanum lycopersicum), a member of the Solanaceae family, are one of the most widely cultivated crops globally due to their nutritional value and extensive culinary use. The global production of tomatoes exceeded 186 million metric tons in 2022, with China, India, and the United States being the leading producers (FAO, 2023), In Africa, Nigeria is the second-largest producer in Africa behind Egypt, yielding approximately 4 million tons annually (Aina and Adewole, 2025). Despite this impressive output, the nation spent over ₦16 billion (about $38 million) on 105,000 metric tons to import tomato paste between 2018-2020 (Alimi. 2021). This paradox is driven largely by biotic constraints and a staggering post-harvest loss rate of about 45%, equating to nearly 1.8 million tons of wasted tomatoes annually (Aina and Adewole, 2025).

Diseases such as early blight (Alternaria solani), late blight (Phytophthora infestans), and root-knot nematodes (Meloidogyne spp.) pose severe threats to tomato production. Early blight has been associated with up to 86% yield loss in Nigeria and other parts of the world (Parvin, *et al.,* 2021). In South-Ethiopia, losses from late blight range from 63.7% to 100% (Negesa and Ayana, 2021). Root-knot nematodes significantly reduce nutrient absorption in plants leading to stunted growth and severe yield losses. In northern Nigeria, root-knot nematode infestations are estimated to cause yield losses of up to 40% (Onyeke and Akueshi, 2012).

There is therefore an urgent need for an intelligent, scalable, and adaptive solution for early detection, real time diagnostics and control of these diseases. A decentralized federated ensemble deep learning approach offers a promising pathway. In a region where disease outbreaks and data scarcity are common, such a system could transform tomato production, minimize crop losses, reduce import dependency, and ensure sustainable economic gains.

II. Literature Review

Plant disease detection using artificial intelligence (AI) and deep learning (DL) techniques has seen considerable progress in recent years. Traditional image processing methods have given way to more accurate, data-driven approaches powered by convolutional neural networks (CNNs), which have demonstrated high performance in tasks such as leaf classification, segmentation, and disease severity estimation (Mohanty *et al*., 2016). Despite these advancements, existing models often rely on centralized training and curated datasets, which pose limitations in terms of scalability, privacy, and regional specificity.

Several works, such as Ferentinos (2018), have illustrated the capability of CNNs to detect multiple crop diseases with over 99% accuracy using controlled datasets. Similarly, the PlantVillage dataset, widely used for training DL models, has enabled the development of robust classifiers for tomato diseases. However, models trained on such datasets often fail to generalize effectively when applied to heterogeneous, real-world farm conditions typical in regions like Nigeria. This points to a critical gap which is the lack of localized data and models capable of adapting to diverse agroecological conditions.

To address this, recent studies have begun exploring federated learning (FL) frameworks in agriculture (Kumar et al., 2021; Li *et al*., 2025). FL allows model training on decentralized data sources without compromising privacy, an essential feature for agricultural stakeholders concerned with data ownership. Yet, most implementations have been limited to simple classification tasks and do not incorporate ensemble architectures or advanced image segmentation, both of which are crucial for detailed disease detection and actionable insights. Moreover, few of these systems are adapted to mobile deployment or local incentive mechanisms that promote farmer participation.

On the ensemble front, combining multiple deep learning models has proven effective in enhancing classification accuracy and robustness (Ganaie *et al*., 2022). Vision Transformers (ViTs), though relatively new, have been shown to outperform CNNs in capturing long-range dependencies in visual data (Dosovitskiy *et al*., 2020). U-Net, meanwhile, excels in medical and agricultural image segmentation due to its encoder-decoder structure and skip connections, enabling pixel-level disease localization (Ronneberger *et al*., 2015). Despite these model-specific advantages, an integrated architecture that combines CNNs, ViTs, and U-Net in a federated setting remains largely unexplored in agricultural AI.

Furthermore, the integration of blockchain and smart contracts into agricultural AI systems is an emerging research frontier. Blockchain has been proposed for securing agricultural data and validating transactions (Tian, 2017), but its combination with federated learning in plant disease detection is still novel. Using the InterPlanetary File System (IPFS) for decentralized data storage and employing smart contracts to manage incentives for data contribution and validation represent pioneering approaches that address the dual concerns of transparency and sustainability in data-driven agriculture.

Hybrid intelligent systems have been recognized for their effectiveness in modeling uncertain and complex agricultural problems. Harisu Abdullahi *et al*. (2025) developed a hybrid fuzzy–neural expert system for agricultural decision support, specifically targeting tomato pests and diseases. Their model combined fuzzy logic, which captures uncertainty and linguistic knowledge, with neural networks, which are capable of learning from large datasets. This synergy provided a knowledge representation framework that enabled farmers to make informed decisions regarding pest and disease management.

The strength of this approach lies in its adaptability and robustness in handling non-linear agricultural data. Unlike conventional rule-based systems, the hybrid fuzzy–neural model offers a self-learning component that enhances predictive accuracy over time. However, challenges remain in terms of scalability, as real-world deployment requires continuous updates of rules and integration with IoT sensors for real-time monitoring. The study illustrates how merging symbolic and sub-symbolic AI can significantly enhance agricultural decision support systems.

Traditional centralized machine learning frameworks often require the aggregation of large-scale farm data in a single repository, raising concerns about data privacy and ownership. To address this, federated learning (FL) has emerged as a promising paradigm. Mamba *et al*. (2023) proposed an image-based crop disease detection framework using federated learning, which enabled collaborative model training across multiple devices without transferring raw data.

This approach not only preserved data privacy but also allowed for a diverse range of crop images to be utilized in model training. The federated model demonstrated improved generalization across heterogeneous farming environments compared to centralized models. Importantly, the system empowered smallholder farmers to contribute to model updates while retaining ownership of their agricultural data. Nevertheless, challenges such as communication overhead, model convergence, and handling unbalanced datasets persist. The study marks a significant step towards decentralized and privacy-preserving smart farming solutions.

The shift towards precision agriculture emphasizes localized, data-driven interventions for crop growth monitoring and disease management. Imtiaz *et al*. (2022) proposed a peer-to-peer (P2P) machine learning platform that facilitated knowledge sharing among farmers for crop growth and disease monitoring. Their framework integrated distributed machine learning algorithms with peer-to-peer communication protocols to enhance decision-making.

This decentralized approach fosters collaboration and democratizes access to agricultural intelligence, reducing reliance on centralized servers or institutions. By leveraging local computational resources, the P2P platform enhances scalability and resilience. However, the heterogeneity of devices and variable internet connectivity in rural areas present challenges to its large-scale deployment. This model reflects the growing importance of community-driven knowledge exchange in the future of agriculture.

The work of Olotu, *et al* (2025) presented a decentralized ensembled deep learning model tailored for the early detection and control of tomato plant diseases, addressing critical challenges in food security and sustainable agriculture. By leveraging ensemble learning within a decentralized framework, the study enhances accuracy while ensuring data privacy and reliability across diverse farming environments. This work makes a valuable contribution by combining technical innovation with practical applicability, offering a scalable solution for modern agricultural systems (Olotu *et al*., 2025).

AI has also been integrated into smart agriculture systems for disease detection and crop management. Mitra *et al*. (2022) examined how smart agricultural practices, enhanced by AI, can transform farm operations. Similarly, Oyewo *et al.* (2021) presented a framework for mitigating disease infestation in selected plants using artificial intelligence-based detection techniques. Their approach leveraged deep learning algorithms for early detection of plant diseases, which allowed for timely interventions and minimized crop loss.

These studies highlight the potential of AI in improving agricultural resilience by providing real-time monitoring, predictive insights, and automated interventions. The limitations, however, include high computational demands, the need for large labeled datasets, and the difficulties of transferring models across different crop species and geographic regions.

Beyond AI and federated learning, IoT and blockchain technologies have been increasingly explored to improve crop management systems. Vitali *et al*. (2021) provided an interdisciplinary survey on IoT applications in crop management, identifying the role of interconnected devices in monitoring soil health, irrigation, and crop disease prevalence. IoT sensors enable the collection of continuous data streams, thereby enhancing the precision of agricultural interventions.

Hassija *et al*. (2021) advanced this discourse by proposing a blockchain and deep neural networks-based framework for enhanced crop protection. Blockchain ensured data security, immutability, and trust among stakeholders, while deep neural networks provided accurate disease detection. The integration of blockchain with AI and IoT creates a transparent, secure, and automated ecosystem for agricultural decision-making. However, high energy consumption and technical complexities remain barriers to adoption, especially in resource-constrained farming communities.

The reviewed literature underscores a progressive movement towards decentralized, intelligent, and secure agricultural systems. Hybrid fuzzy–neural approaches (Harisu Abdullahi *et al.,* 2025) emphasize the importance of combining symbolic reasoning with machine learning. Federated and P2P learning frameworks (Mamba et al., 2023; Imtiaz et al., 2022) highlight privacy, collaboration, and democratization of agricultural intelligence. AI-driven detection systems (Mitra et al., 2022; Oyewo *et al*., 2021) demonstrate high accuracy in disease prediction, while IoT and blockchain frameworks (Vitali *et al.,* 2021; Hassija *et al.,* 2021) ensure secure and transparent data management.

Despite these advances, critical gaps remain. First, most models are tested under controlled or limited field conditions, raising concerns about scalability in diverse agro-climatic zones. Second, challenges such as data imbalance, limited internet infrastructure, and high energy consumption constrain the real-world deployment of these systems. Third, the integration of multi-technology frameworks combining federated learning, blockchain, IoT, and hybrid AI models remains underexplored. Addressing these gaps will be crucial in realizing sustainable and inclusive smart agriculture.

This work introduced a novel ensemble deep learning architecture merging CNN, ViT, and U-Net within a federated learning framework tailored for heterogeneous and privacy-sensitive agricultural data. It addresses the lack of real-time, field-applicable systems by incorporating mobile-based deployment and farmer-facing interfaces. It also innovatively integrates blockchain and IPFS technologies to provide immutable recordkeeping, secure data sharing, and a token-based incentive structure for stakeholder engagement.

By grounding model development in both local farm data and globally available datasets like PlantVillage, the research ensures contextual relevance while maintaining generalizability. The scientific contributions thus span across technical innovation, practical deployment, and societal impact. These contributions include a federated ensemble architecture that combines CNN, ViT, and U-Net to enhance accuracy and disease segmentation; a decentralized framework that ensures data privacy, ownership, and regulatory compliance; the integration of blockchain and IPFS for secure, transparent, and traceable model operations; and a smart contract–based reward system that incentivizes data sharing and expert validation.

III. Materials and Methods

This research adopts a hybrid data-driven and decentralized artificial intelligent approach to detect tomato plant diseases using a federated ensemble deep learning model, specifically focused on agricultural regions in Nigeria. The methodology comprises five core phases: data collection, data preparation, model development, decentralized implementation, and evaluation.

The dataset for this study will be sourced from three channels: two primary and one secondary. The primary data will be obtained from “Lead Impact Farm” located in Akure, Ondo State, Nigeria and my personal farm, both located in Nigeria’s tomato-producing regions. These datasets will include real-time images and sensorbased crop features such as leaf color, shape, and size, stem strength and pigmentation, flower and fruit development, and physiological parameters like moisture level and temperature. Secondary data will be accessed from PlantVillage, a publicly available repository that includes annotated plant disease images. The aim is to gather a representative sample of tomato leaf images and crop characteristics under various conditions prevalent in Nigeria, ensuring sufficient diversity in disease type and environmental background.

The collected data will be pre-processed to ensure consistency and readiness for model training. Data augmentation techniques such as flipping, rotation, contrast enhancement, and cropping will be used to synthetically expand the dataset, prevent overfitting, and improve the model's generalization capacity across various tomato plant disease conditions.

The deep learning architecture will combine Convolutional Neural Networks (CNN), Vision Transformers (ViT), and U-Net. CNN will be used to extract local texture features, edges, and spatial patterns, while ViT will handle global contextual relationships. U-Net will provide pixel-level segmentation and disease localization. The model pipeline processes raw images into high-dimensional feature maps via multiple convolutional, pooling, batch normalization, and dropout layers. The final output is a classification and segmentation mask used for identifying disease presence and severity.

To enhance transparency and scalability, the model will be deployed on a decentralized framework. A federated learning system will be used, where farmers' local devices or edge nodes train the model independently using their data, without uploading raw images to a central server. Only model parameters (weights) are shared and aggregated using a global optimizer. Blockchain technology will facilitate data integrity and security. IPFS (InterPlanetary File System) will be used to store model results, each identified by a unique CID (Content Identifier).

Smart contracts deployed on Ethereum will handle validation of results through a crowd-sourced voting mechanism among experts. In addition, a token-based incentive system will reward contributors (farmers, researchers, or verifiers) for sharing data and validating results. This will encourage sustainable data contribution and expert participation.

Upon building the models, the models will be deployed on a mobile application that can work across different mobile operating system platforms. Authentication will be managed through cryptographic public/private keys and tokenized session controls.

This methodology ensures robust, privacy-preserving, and locally adaptable detection of tomato diseases in Nigeria's agricultural systems.

System Architecture and Design Principles

The system architecture was formulated based on both technical considerations and the practical realities of agricultural environments. The architecture is shown in figure 1.0

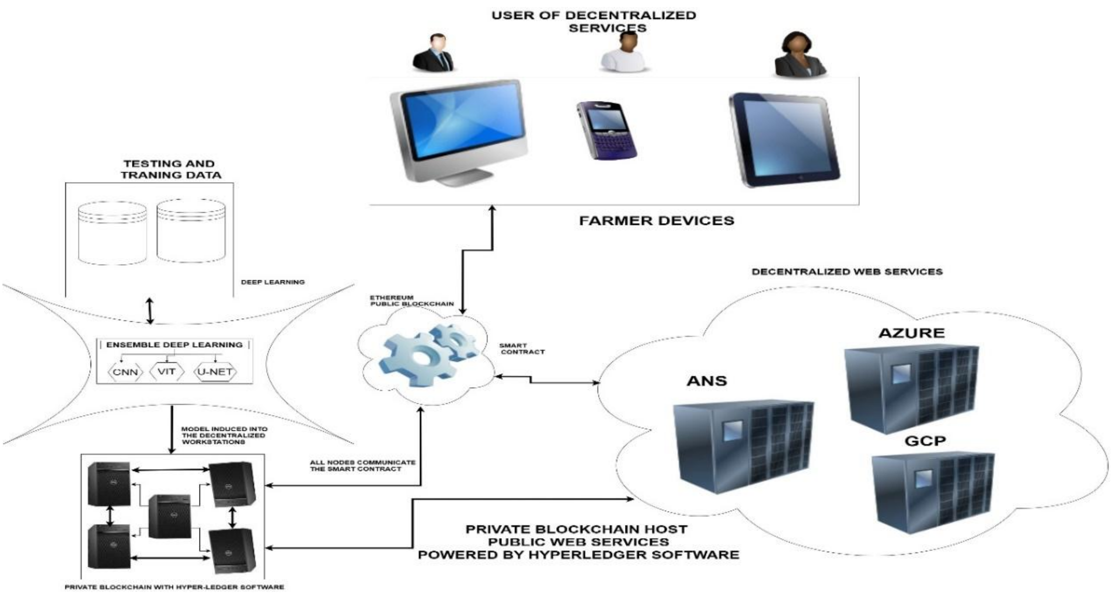

Figure 1.0 Architecture of the system.

Data Collection:

Data will be collected from three sources, two primaries; ("Lead impact farm", my personal farm,) and one secondary source (PlantVillage). Crop features such as growth parameters, which includes; Leaf Color, Leaf Shape and Size, Stem Strength and Color, Flower and Fruit Development, Overall Plant Vigor, Moisture Levels, Temperature and Humidity, Nutrient Levels etc, will be necessary for development of effective control system.

Data preparation
In order to get the optimal results of all the images will have to be identical in resolutions and classes, all images will be re-scaled and color toned to get an identical-looking dataset. All the images will be resized to 256 × 256 and further passed on to the deep learning module this make our solution robust to input image size differences. As shown in Algorithm below:

Algorithm for Data processing

Procedure CONVERT – IMAGE (Image)

*i*mage < - RE-SIZE IMAGE (Image)

*i*mage < - BRIGHTEN IMAGE (Image)

*i*mageArray < - CONVERT TO ARRAY (Image) NumPy array

*i*mageArray < - SCALEARRAY→Divide value by 255 (normalization)

Return ImageArray

End procedure

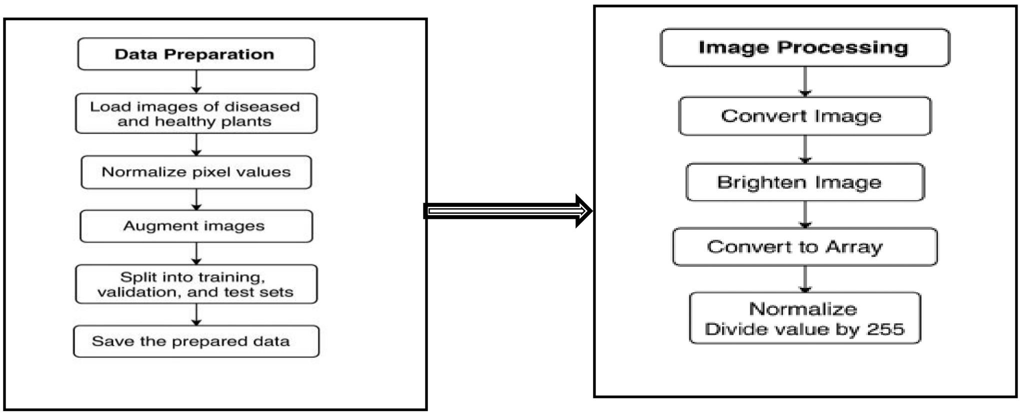

Figure 2.0 Algorithm for Data processing and Image Processing

Figure 2.0: **Algorithm for Data processing**
The complete ML pipeline encompasses the entire lifecycle from data collection through model deployment and continuous improvement through federated learning, demonstrating a comprehensive approach to agricultural AI system development. The pipeline begins with data collection and preprocessing, where raw tomato leaf images undergo systematic augmentation and normalization to create a robust training dataset. The training phase employs the hybrid CNN-ViT architecture with sophisticated optimization strategies including adaptive learning rate scheduling and class-weighted loss functions to address dataset imbalance.

The federated learning extension represents a significant innovation in the ML pipeline, enabling continuous model improvement through privacy-preserving collaboration among farmers worldwide. This approach addresses the fundamental challenge of learning from diverse regional disease patterns while maintaining strict privacy guarantees for agricultural data. The federated learning pipeline operates in parallel with the inference system, allowing farmers to contribute to global model improvement without sharing their sensitive farm data

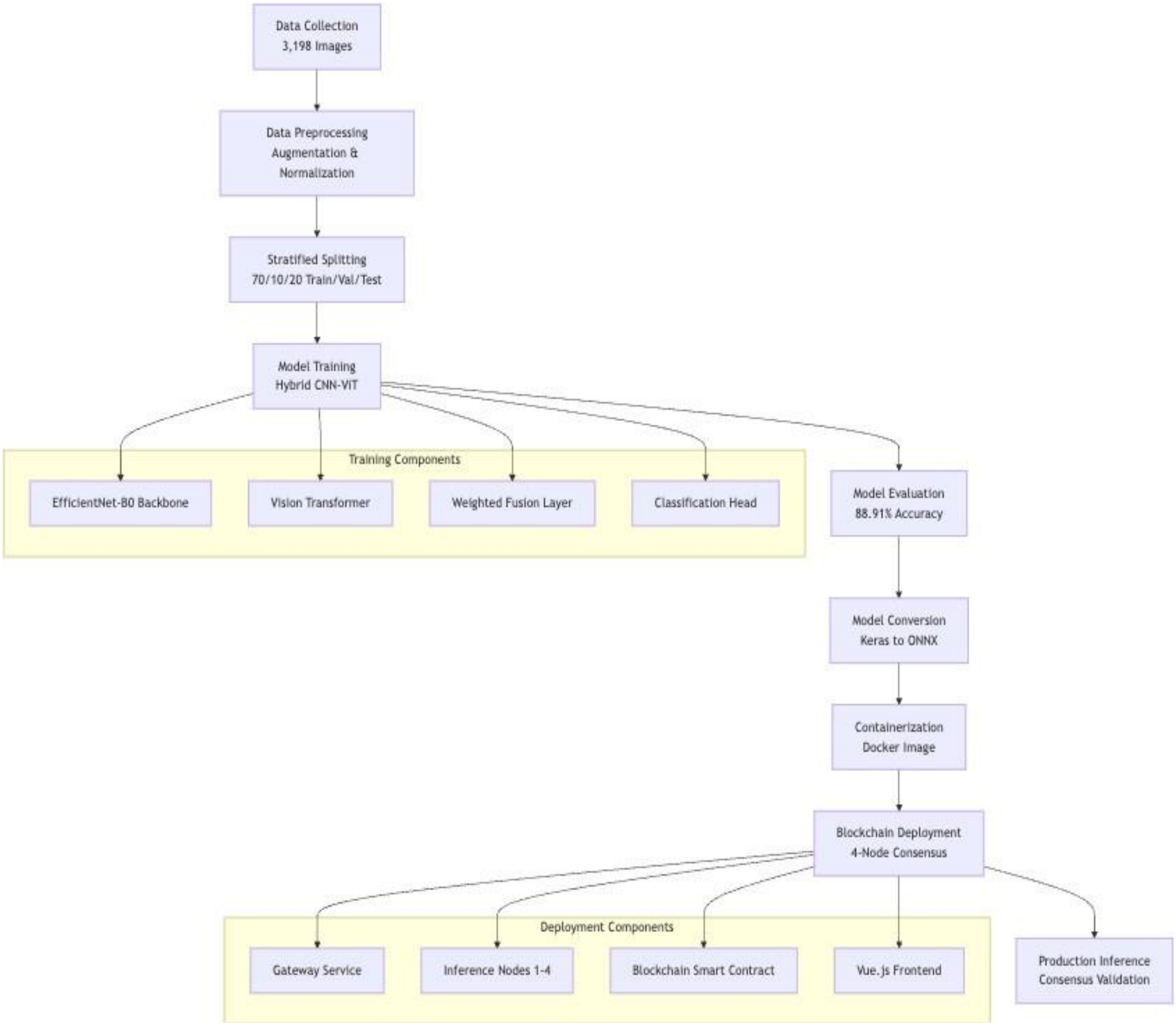

Figure 3.0 Machine Learnimg Pipeline and DevOps Process

Data Augmentation:
Augmentation techniques like rotation, flipping, cropping, and contrast adjustments to increase the dataset's diversity. This helps prevent overfitting and improves model generalization.
Deep Learning Module: The deep learning module is made up of the following:

i. The convolutional neural network model (CNN)
ii. The vision transformer model (ViT)
iii. The U-net model (U-net)

CNN extract local features like textures, edges, and shapes, help detect early signs of disease on tomato leaves. A custom CNN is designed to extract important visual features from the images. Input images are transformed to high dimensional feature maps.
A review of existing works on plant diseases detection will be carried out. The decentralized federated ensemble deep learning model for detection of plant diseases comprises of several integral modules: Data collection, Ensemble deep learning, Decentralization and Federated learning Modules.
Data preparation will be done to get the optimal results of all the images by re-scaling and color-toning to get an identical-looking dataset. The ensemble deep learning module is made up of the convolutional neural network model (CNN), the vision transformer model (ViT), and the U-net model (U-net). CNN extract local features like textures, edges, and shapes sent as input images which is transformed to high dimensional feature maps at the convolution layer which is expressed in equation 1:

$$f(x, y) = \sum_{i=1}^{kh} \sum_{j=1}^{kw} I(x+i, y+j) * k(i, j) + b \quad (1)$$

where I(x, y) is the pixel value of the input image at position (x, y), $k(i, j)$ is the convolution filter of size $k_h \times k_w$ applied to the images, b is a bias term, $f(x, y)$ is the output feature map. An activation function ReLU (Rectified Linear Unit) is applied to introduce non-linearity into the model expressed in equation 2:

$$ReLU_{(x)} = \max(0, x) \quad (2)$$

where x is the output from the convolution operation.

ViT divides the input image into patches and flattens each patch into a vector, a positional embedding E_{pos} is added to each patch embedding to provide information about the position of the patch in the original image expressed mathematically in equation 3 below:

$$z = [x_{cls}; + E^{1}_{pos};\dots; x^{N}_{p} + E^{N}_{pos} \quad (3)$$

where x_{cls} is a special classification token (learnable), N is the total number of patches.

The Self-attention allows ViT to capture global relationships between all patches using a scaled dot-product attention mechanism.

The scaled dot-product attention is then computed as expressed in equation 4:

$$Attention(Q, K, V) = softmax\left[\frac{QKT}{\sqrt{dk}}\right]\text{V} \quad (4)$$

where QK^T is the dot product between the will be captured by comparing each patch with every other patch, allowing the model to globally aggregate information, d_k is the dimensionality of the key vector used to scale the dot product, V is the value vector, which is weighted by the attention scores.

The local features F_{CNN} from the CNN and global features F_{ViT} from ViT are combined through a weighted sum expressed in equation 5:

$$F_{\text{combine}} = \alpha * FCNN + (1 - \alpha) * FViT \quad (5)$$

where α is a learnable parameter or a hyperparameter controlling the contribution of local and global features. The combined feature maps are then fed into the MC-U-Net for pixel-level classification.

The encoder applies a convolution followed by max-pooling to downsample the combined feature maps expressed mathematically as:

$$F^{(I)}_{enc} = ReLU(W(l) * F^{(l-1)}_{combined} + b(l)) \quad (6)$$

$W^{(l)}$ is the weight matrix of layer, $*$ denotes convolution, $F^{(I)}_{enc}$ is the downsampled feature map at layer l.

The decoder upsamples the feature maps using transposed convolutions to recover spatial resolution expressed as:

$$F^{(I)}_{dec} = ReLU(W^{(l)}_{dec} *^{T} F^{(l)}_{enc} + b^{(l)}_{dec}) \quad (7)$$

where: $*^{T}$ represents transposed convolution. Each pixel is classified into one of the classes using a softmax function over the channels expressed as:

$$y(x, y) = softmax(w_{\text{out}} * F_{dec}(x, y) + b_{\text{out}}) \quad (8)$$

where y(x,y) represents the predicted class probabilities for pixel (x,y) w_{out} and b_{out} are the weights and bias for the final output layer.

Decentralization will be achieved by leveraging blockchain technology and smart contracts, each result is given a content identifier (CID), which is a unique hash representing the result mathematically as:

$$\text{CID} = \text{H(R)} \quad (9)$$

The smart contract will distribute the CID to a predefined group of verifiers; each verifier submits their agreement or disagreement with the classification result mathematically expressed as:

$$\text{SC(R)} = \begin{Bmatrix} Valid(R) & if \sum_{i-1}^{N} Votei \geq T. \\ Invalid(R) & otherwise \end{Bmatrix} \quad (10)$$

Where $vote_i$ is the vote from the i-th verifier, N is the total number of verifiers, T is the threshold percentage required for validation. A token-based incentive system will be implemented through smart contracts also, such that participants (farmers, experts, researchers) will be encouraged to contribute their data (e.g., tomato leaf images or feedback on disease classification). formulated as:

$$T_{\text{i}} = \alpha C_{\text{i}} \quad (11)$$

Where α is a proportionality constant set by the smart contract to determine the reward rate.

The central aggregator through federated learning collects the locally updated model parameters and aggregates them to improve the global model, if w_t represents the model weights trained by the i-th node (farmer) at time t, then the global model weights $w_{t+1}$are computed as;

$$WT + 1 = \sum_{i=1}^{N} \frac{nI}{n} w^{i}_{t} \quad (12)$$

Where: n_i is the number of data samples at node i, n is the total number of data samples across all nodes.

IV. Conclusion

This work presented a hybrid CNN-ViT based system to enhance tomato disease classification while integrating blockchain-based deployment strategies for reliability and scalability. In the future, the Python programming language will be used to further refine the framework while a professional web-based application will be designed for farmers to interact with the system, query disease conditions, analyze crop health, and receive validated AI-powered recommendations through the blockchain consensus mechanism.

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